Add on Navigation and Control System for Outdoor Autonomous Wheelchairs for Physically and Mentally Challenged People

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***Abstract*— People with serious physical and/or mental disabilities, such as those with spinal cord injury, muscular dystrophy, dementia, etc., cannot benefit from available powered wheelchairs to gain independent mobility. The objective of this paper is to provide a preliminary design platform of an autonomous wheelchair generation capable, in the long run, of helping people with severe disabilities gain independent mobility. A high-level design, design details and development are provided in this paper. The design was extensively tested on the Tennessee Technological campus. Local media outlets presented a demo and interviewed the designers.**

Keywords- Physically challenged people; mentally challenged people; autonomous; deep learning; electric wheelchair; navigation and control.

I. INTRODUCTION

About 2.3 million people become disable each year in the United States [1]. Such accidents may lead to severe disabilities. According to the World Health Organization (WHO), dementia is one of the major causes of disability and dependency among older people globally [2].

Manual wheelchairs were originally invented to help some of the partially physically challenged people. Unfortunately, these devices are not as helpful to those who lack the strength or awareness to physically propel the wheelchair themselves. To solve this problem, electric wheelchairs were invented. A modern electric wheelchair is shown in Figure 1. While the user can just push a joystick with minimal strength to steer the wheelchair, there are still millions of people with severe disabilities that cannot benefit from such wheelchairs [3].

Recent advances in commercial electric wheelchairs have focused on adding alternative user control modules such as navigating based on the gaze or head tilt of the user, hand gesture control, or even voice control which would allow mobility for people of varying disabilities such as paralysis or amputees; however, these devices still fail to cater to so many [4]. This is because each solution still requires the user to have some level of muscular strength and complete awareness of the environment around the wheelchair, the destination he or she is trying to reach, and the path needed to reach the destination.

Figure 1. A Modern Electric Wheelchair.

For indoor or outdoor autonomous wheelchairs, the challenging task for a wheelchair is to localize itself in a self-generated map. For indoor navigation, this may be achieved using a Light Detection and Ranging (LiDAR) for Simultaneous Localization And Mapping (SLAM) [5]. Another localization technique uses wireless access points in each room [6].

Four outdoor navigation, autonomous wheelchairs have to navigate wide areas in unknown environments and changing sceneries. In such cases, indoor localization and mapping techniques cannot cope with environment variabilities in wide areas and similarities of features in different geographical locations in the areas to be autonomously navigated. LiDAR range is limited, and its accuracy is reduced with range. Wireless access point solution is too expensive.

For outdoor autonomous wheelchairs, several designs have been proposed. In [7], the authors use a camera to track a yellow line to navigate the wheelchair for people with walking disability. For a fully autonomous wheelchair, this approach is not reliable whenever the line paint becomes old or obstructed. Furthermore, this design does not allow for obstacle detection and avoidance. Finally, this design does not allow for localization of the wheelchair. In [8], the authors use voice command control to navigate the wheelchair. This assumes that the driver has full mental capacity to generate proper control commands and the sense of direction of where to go. In [9], the authors use a web-based mission planning and teleoperation and monitoring for

 ISBN: 978-1-68558-180-0

the disabled person and the care giver. This is only an assistive approach as it keeps the care giver in the loop. In [10], deep learning was used to help visually impaired users.

High end Global Positioning System GPS and inertial navigation system were used to provide the autonomous navigation in [11], while landmarks were used for the same purpose in [12]. The location provided by a GPS may not be always reliable, especially whenever interferences, crowded area, and severe weather conditions are present. The use of landmarks is not an economical solution, especially whenever the travel distance is long, and requires maintenance.

The proposed solution takes advantage of already existing maps such as OpenStreetMap [13][14] and uses machine learning to provide a fully autonomous solution for navigation on sidewalks that can be used by a wide segment of people with physical and/or mental disability.

The rest of this paper is organized as follows. In Section II, the high-level conceptual design of the autonomous navigation and control system is presented. Section III contains the hardware and software requirements. Section IV overviews the system operation. Section V contains conclusions and future work.

II. HIGH-LEVEL CONCEPTUAL DESIGN

An important feature of the proposed design is to use already available mapping knowledge in the form of digital maps of the area to be navigated area. In this paper, Open Street Map will be used to provide the digital map the wheelchair will use for navigation from one location to another. Open Street Map is an online collaborative map of the entire world that can be accessed through the open-source Python API OSMNx [13]. From this API, one can gather information, such as building names, street names, sidewalk layouts, construction areas, road layouts, sidewalks, intersections, and much more. In this paper, the focus is on the sidewalk layout and building names/locations of the navigation area. An example of Open Street Map of all the sidewalks of Tennessee Technological University TTU campus is shown in Figure 2. In this map, 1 inch corresponds to 430 ft. Given the Open Street Map of the area where the user lives, he/she can use his/her house/apartment as the origin of a relative coordinate system, then express every point on the original map with respect to the chosen origin to make it a local digital map.

The proposed system has two levels of navigation and control: A high and low levels, Figure 3. The high-level uses the local digital map, acquires information from the onboard sensors and sends a control command to the low-level control. Such commands include obstacle avoidance, move forward, turn left or right, etc. The low-level control translates the commands to control signals applied to the drive motor.

Figure 2. TTU Campus Sidewalks provided by OpenStreetMap.

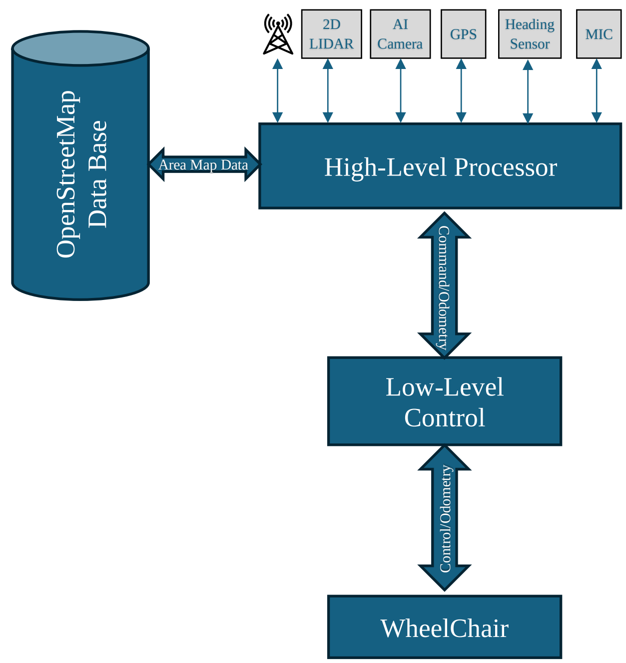

Figure 3. High-Level Conceptual Design of the Navigation and Control System.

III. HARDWARE AND SOFTWARE REQUIREMENTS

In this work, the only requirement from the user is to tell the system the destination location such the name of a building. This can be achieved via a vocal command or by a care giver via wireless communication. The navigation and control system must perform several tasks: host the digital map of the navigation area, execute obstacle avoidance, keep the wheelchair on the sidewalk of the path to be followed, and keep approximate location of the wheelchair until the destination location is reached. For this purpose, the following sensors are needed: 2D LiDAR for obstacle avoidance, a camera for navigation, and odometry to provide approximate traveled distance, a heading sensor, and a GPS to provide an approximate location of the wheelchair, a microphone, and a wireless communication between the wheelchair and the care giver. Note that the GPS is only relied on to obtain an approximate location in navigation area. Furthermore, the objective here is not to follow accurately the desired path but keep the wheelchair approximately in the middle of the sidewalk using the vision-based sensor.

The software design includes several modules. A high-level summary flowchart is provided in Figure 4.

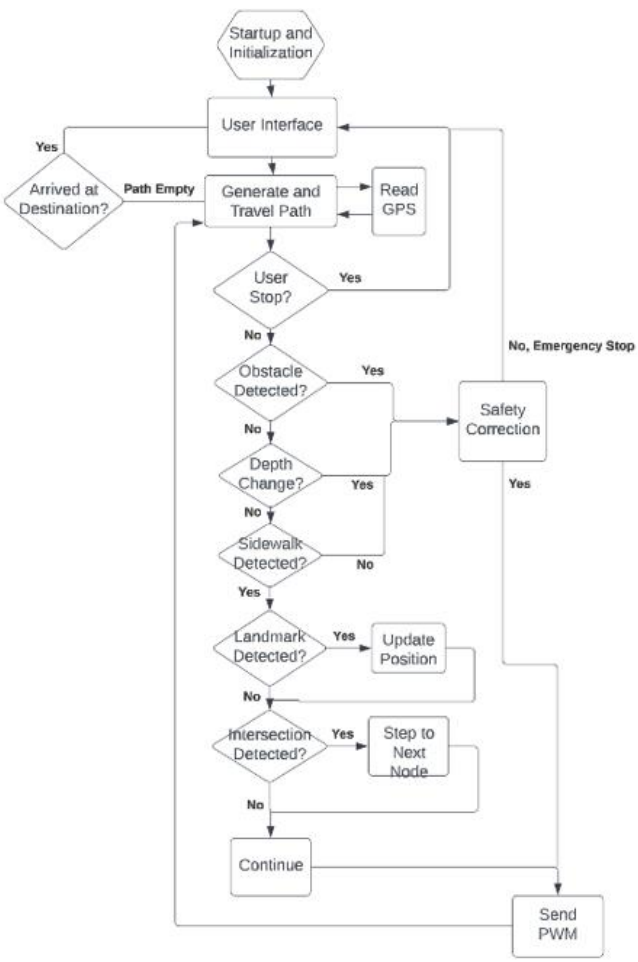

Figure 4. High-Level Software Flowchart.

IV. AUTONMOUS SYSTEM OPERATION

The first task is to use a microphone to tell the wheelchair where its final destination is. It is worth noting that the current location is assumed known such as the front of the house location, where the wheelchair user resides or the name of a building, he/she is at whenever the driver decides to go from one location to another. Then the high-level control system/navigation uses the digital map to determine the shortest path from the chair current location to its final destination. This path consists of a sequence of consecutive segments of the sidewalk. Each segment is characterized by the location of two end nodes and the distance between the two nodes. Given the two nodes, the absolute heading of the line joining the two noes will be determined. The wheelchair has to travel along these segments in the proper order until it reaches its final destination. An example of a generated path going from one building to another is shown in red Figure 5. One major challenge of this control and navigation system is to keep the wheelchair on its intended segment of the sidewalk as it moves toward its destination.

Figure 5. Automatically Generated Shortest Planned Path (in red).

Once a path has been selected, the wheelchair starts with the first segment of the path using the heading of that segment. Using its approximate odometry readings and the known length of the segment, the wheelchair will know that it is about to enter the second segment. At that time, the wheelchair will start turning or continue in the same direction without leaving the sidewalk. Keeping the wheelchair on the sidewalk at all times will use a camera as will be discussed later. The wheelchair keeps track of its position by fusing the information from its odometry and the GPS whenever available, and the heading measurements. Whenever, the wheelchair makes a turn, it will compute the new heading using the two ends of the new segment and uses this new heading as the reference heading and the heading sensor measurements as feedback. Whenever the wheelchair encounters an intersection, it will either go straight, turn left, or turn right, etc. The decision of what to do is based on the planned path and the wheelchair position as it approaches an intersection that is confirmed by the camera sensor. The wheelchair can use its current position on the planned path to predict approximately the next turn and slows down to turn to follow the new heading. If an obstacle appears while traveling, the wheelchair uses the LiDAR information which has enough range to allow the wheelchair to execute the proper maneuver to avoid the obstacle while staying on the sidewalk.

In all cases, the challenge for the wheelchair is to stay on the sidewalk at all times until it reaches its destination. The first solution considered was the use of computer vision-based approach using classical image processing techniques [15]-[19].

Figure 6 shows the performance of lane detection using different edge detection techniques, while Figure 7 shows a sidewalk detection in the presence of grass, where images A and E are raw images of two different scenes.

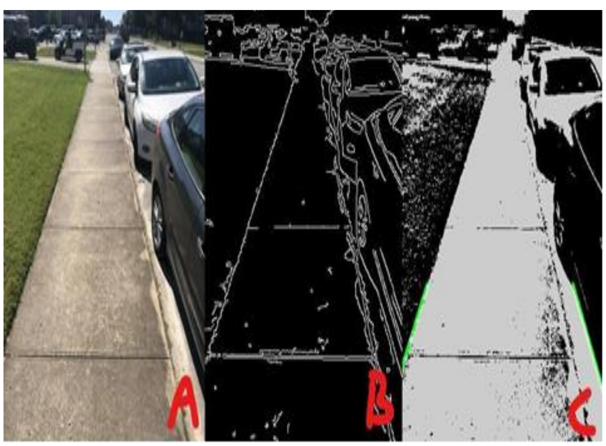

Figure 6. Lane detection. A raw image, B. using edge detection, and C using Hough line transform.

Because of the variability in the images of the sidewalks due to weather conditions, lighting conditions, crowdedness of the sidewalk, and variability of the scenery, classical image processing techniques did not perform well in keeping the wheelchair on the sidewalk. Since the navigation and control operate in real time and given the variability in the images acquired by the camera, a human-like brain is needed to process images with varying pixel density and still extract the sidewalk from such images in order to keep the wheelchair on the sidewalk.

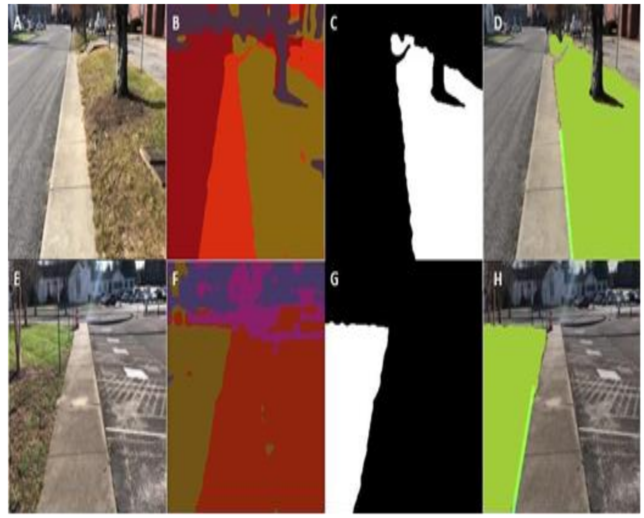

Figure 7. Sidewalk detection in the presence of grass: ((B, F) using the K-Means clustering, (C, G) using color thresholding of the green pixels, and (D, H) using Hough Line.

Artificial Neural Network (ANN) is inspired by the structure and function of neurons in the brain. These networks can take in substantial amounts of data and make inferences based on what it has learned and has previously seen. Much like a brain, the ANN consists of three or more layers of neurons: An Input layer, one or more hidden layers, and an output layer. Each neuron within the neural network has both a weight and threshold. To pass data along to the next neuron this threshold must be surpassed. An example of an artificial neural network is shown in Figure 8, [20].

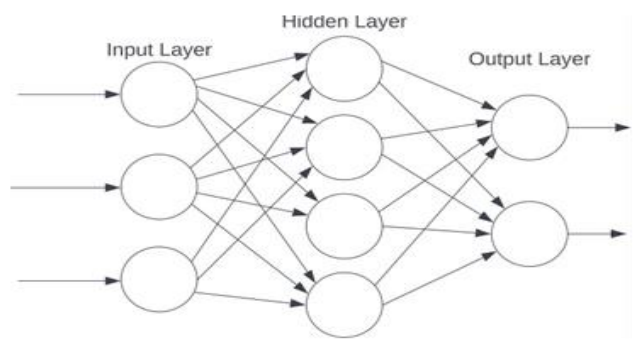

Figure 8. Visualization of a Single hidden layer ANN.

For a complex mapping between the inputs and outputs, more than one hidden layer will be needed. This leads to Deep Neural Networks (DNN) [21]. Because of the increased number of layers, these networks can model complex mapping between inputs and outputs, extract structural knowledge from data, and make inferences from extracted knowledge. Convolutional Neural Networks (CNN) have been extensively used in machine vision [22]. To perform real time semantic segmentation, the bilateral segmentation network (BisNet) and in particular BiseNetV2 architecture is faster than most networks of its type. This is done through the separation of the

 ISBN: 978-1-68558-180-0

network into two separate but parallel branches, detail and semantic [22]-[24]. Figure 6 shows the performance of the BiseNetV2 in detecting sidewalks under different scenarios and conditions. In this figure, images in the first column represent the input image of the sidewalk in front of the wheelchair, the second column is the output masks from the BiseNetV2, and the third column is the predictions applied to the input for visualization. This DNN shows its success in detecting the sidewalk in cluttered environments. Figure 9 shows its performance as far as detecting the sidewalk as well as intersections.

Once a final destination is chosen, the system automatically selects the shortest path to travel from its current location to the final destination. The user may choose to change the final destination while traveling. As discussed previously, a path is mostly a collection of consecutive sidewalk segments. In the absence of a curvature, a segment of a sidewalk is a straight line whose length and orientation may be obtained from the OpenSstreetMap. The navigation and control system use its heading sensor as feedback to follow the reference heading provided by the street map for that specific segment.

The camera/control system are responsible for keeping the wheelchair approximately in the middle of the sidewalk at all times. It is worth noting that the wheelchair does not have to follow a very specific path accurately as long as it remains on the sidewalk without oscillations. Figure 9 shows the performance of BiseNetV2 Model in detecting the sidewalk. Its performance allows the wheelchair to stay on the sidewalk for various sceneries and lighting conditions, Figure 10.

In situations where the system detects an intersection of sidewalks where the wheelchair is supposed to go straight, the system uses the heading sensor information to keep the wheelchair moving without executing a turn. Whenever the wheelchair is close to an intersection in which it is supposed to make a turn, it uses the new heading reference, provided by the path planning at that intersection, and uses the heading sensor as feedback to slowly make the turn to align itself with the new segment of the sidewalk of the planned path.

Figure 9. Performance of BiseNetV2 Model.

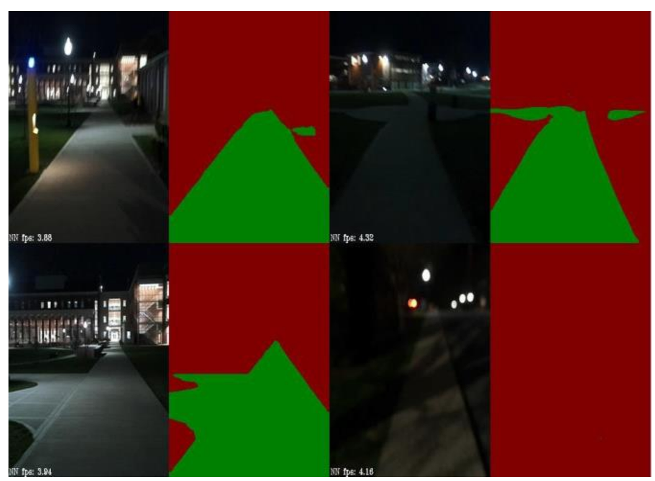

Figure 10. Sidewalk detection at night using BiseNet V2.

V. Conclusions

In this paper, the design of an autonomous navigation and control system that uses digital maps of a navigation areas of interest was developed and successfully tested on an existing wheelchair that can be manually controlled using joystick. The manual control was totally by passed and the proposed system was added to the wheelchair for autonomous outdoor navigation.

Future work will focus on additional testing in different navigation areas. In addition, more safety features will be added to deal with unforeseen situations such as a pothole in the sidewalk and deal with failure recoveries, while ensuring that the wheelchair to come to a complete stop before it leaves the sidewalks. For people with dementia, a feature that has already been designed, but not tested, consists of pushing a "Home Button" to inform the chair that it is time to go back to the user residence.

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 ISBN: 978-1-68558-180-0